Aalto University
School of Science
Master's Programme in Computer, Communication and Information Sciences

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# Analysis of Li-Ion Battery Characteristics in a Wearable Patient Monitoring Device Using Equivalent Circuit Model

Master's Thesis
Espoo, February 22, 2021

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ABSTRACT OF MASTER'S THESIS

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Hospital care is rapidly transforming with the proliferation of Wearable Patient Monitoring devices. These "plug and play" devices are very useful in situations where remote monitoring is required. They are usually battery operated, which render them portable and rechargeable. The rechargeable devices are cost effective and environment friendly. However, the rechargeable batteries which are used in medical devices exhibit non-linear characteristics. The non-linear behaviour is typically due to the chemical reactions which takes place within the cell, and it makes it hard for the designer to predict the battery behaviour. In order to design efficient monitoring systems, it is important to understand the nature of the battery in combination with the power needs of the device. As a solution battery models are implemented which give the designer and developer a tool to gauge battery behaviour in various circumstances. This thesis focuses on sensor devices and their power source i.e. sensor batteries. The rechargeable battery pack consists of three lithium-ion cells that are modeled to predict the performance of the device. Experimental test data is collected using the Cadex C8000 battery analyzer test setup. Data collected from battery testing is used to validate a modified Thevenin's Equivalent Circuit model. The experimental test data and simulated output from the battery model are compared and evaluated to create an optimized model which can estimate the performance of a battery pack.

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|---|---|
| **Keywords:** | battery modeling, wireless patient monitoring, sensor devices, equivalent circuit model, battery life, non-linear characteristics |
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Tanvi Jain

# Abbreviations and Acronyms

| | |
|---|---|
| IoT | Internet of Things |
| CPU | Central Processing Unit |
| NIC | Network Integration controller |
| SEI | Solid Electrolyte Interphase |
| OCV | Open circuit voltage |
| SoH | State of Health |
| SoC | State of Charge |
| BMS | Battery Management System |
| ECM | Equivalent Circuit Model |
| WSN | Wireless Sensor Network |
| MCU | Microcontroller Unit |
| KiBaM | Kinetic Battery Model |

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# Chapter 1

# Introduction

The mushrooming of wireless devices in the field of medical science has created a huge demand for low power consumption design techniques. These design techniques must strike the right balance between the low energy consumption and high performance of the system to meet the consumer demands of practical and efficient devices. Subsequently, they must answer: how to build a wireless device which provides maximum throughput, portability and reach-ability under different load profiles, using optimum power for long duration. Alternatively, how to schedule processes inside wireless device such that battery lifetime remains unaffected for longer duration.

In order to schedule battery-friendly processes, a huge amount of batteries and processing devices would be required to collect huge amount of battery cycling data. Such a task can become tedious and error prone due to several reasons which include the size of data, duration of data collection and changing ambient conditions over that duration. Modelling is a way to quickly cycle the batteries for required output. This reduces the involved cost and time. Battery models provide useful battery characteristics as output which can then support the design and development of energy efficient wireless devices with excellent battery capacity.

This project aims towards studying, analysing and developing a battery model for Patient Monitoring devices. The objective is to build an equivalent circuit battery model for a wireless device, by using parameter estimation and optimisation techniques. This work has been carried out at GE Healthcare, Helsinki. The site at Helsinki specializes in Hardware/Software design, development and testing of the Wearable Patient Monitoring devices.

## 1.1 Motivation

Recent studies have shown that the world population is ageing quite rapidly. UN global population projections and estimates have shown that in 2018, for the first time ever, the people aged 65 and above have outnumbered the children aged under five [5]. More projections show that this trend will continue and by the year 2050, the number of people over 65 years of age will be more than people under age 24. Another UN study projects that by mid century 68% of the world population will be living in urban areas [6]. These two studies indicate a huge rise in demands of sustainable, reliable and robust healthcare solutions for this dominant ageing population. The future demands optimum healthcare designs which will tackle challenges such as availability, durability, longevity, sustainability and re-usability.

Rechargeable Batteries are the prominent renewable energy sources, providing power to these healthcare devices of the future. They are rapidly capturing the markets once dominated by fossil fuels. Furthermore, rechargeable batteries provide energy autonomy that supports mobility, making them an ideal choice for all portable electronic devices. However, for the development of successful device, it is important to choose the battery of appropriate size and capacity. This choice should be made very early in the design phase of these devices for better performance and failure avoidance. Battery models can be used for estimating battery characteristics and behaviour under different load profiles. These behavioural data help in choosing right battery for the task while avoiding costs of cycling several batteries for long hours.

## 1.2 Problem statement

Wearable patient monitoring solutions are battery powered real time systems which are energy constrained. The hardware components which are responsible for power consumption are e.g. CPU, Wifi NIC, Bluetooth, accelerometer, LCD, Touch Sensors and speaker. Each component is in several operating modes i.e. sleep, active, listening, transmitting/receiving while draining a different amount of power. The components consume power based on the power state they are in and the power state may change based on the utilization of that component. These states combined with their energy consumption rate can be used to prepare a workload model for estimation of the energy consumed by each component.

However, this estimation will not consider the variation caused by **internal non-linear effects** of the battery. The non-linear effects are the properties of battery which prevent the batteries from providing constant amount of charge for all types of discharge loads. The non-linear behaviour means that the capacity drops suddenly when battery is subjected to large discharges. This may arise due to change in the chemical reactions caused by varying operational conditions e.g. high temperature may increase the rate of electrochemical reactions, current magnitude and direction may change the reaction type.

To capture these non-linear internal battery behaviour, many battery models have been proposed in the past. There are various battery models which are in use such as analytical battery model [21, 38], stochastic battery model [21], electrical battery model [17] and electrochemical battery model [14]. The usability of each model depends on the application for which they are intended to be used. The complexity and computational cost of the model further governs their usability. Therefore, the problem and aim is to find an appropriate battery model for wireless patient monitoring device.

This thesis is intended to understand the energy consumption of wireless sensor nodes and methods to measure and monitor their energy consumption for energy aware design and development in future. Therefore, the following research questions form the basis of the thesis:

**RQ1**. What is non-linearity of the battery characteristics?

**RQ2**. How does non-linearity affect systems design?

**RQ3**. What are the various ways in which wireless sensor nodes consume power?

**RQ4**. How can we design equivalent circuit battery model to estimate the battery parameters?

## 1.3 Structure of the Thesis

Chapter 2 explains the basic characteristics of Lithium ion Battery along with the various modeling techniques which are used to capture the non-linear behaviour of the batteries. Chapter 3 describes the battery power consumption in context with the sensor devices. Chapter 4 describes popular models available in literature as well as in practice, followed by discussion on the development of simple dynamic electrical circuit model and the experimental setup. It also describes the modeling and simulation in which the results of the dynamic data of cell are compared with the results of electrical equivalent circuit model of the cell. Chapter 5 evaluates the model response of 1RC circuit model in comparison to the 2RC circuit model. Chapter 6 and Chapter 7 gives conclusion in which the description of work summary and work to be done in future are explained.

# Chapter 2

# Background

In this chapter, we will first highlight the physical and electrochemical properties of the battery, then we will discuss various ways in which the battery performance degrades, followed by more elaborate discussion on the dynamic nature of the battery. Then, brief introduction to one of the applications of Battery Model i.e. Battery Management System (BMS). At the end, a discussion on various Battery models and their comparison is provided.

## 2.1 Fundamentals of Lithium-ion Battery

The word 'Battery' is often used as a hypernym to define a certain type of electrochemical power sources. They can be single cell or pack of cells. However, there is a technical difference between a cell and a battery in terms of the way they are packed. A cell is a basic electrochemical unit, whereas batteries are two or more cells that are connected electrically to receive, store and deliver electric energy. Two or more cells are connected side by side or packed as one single physical unit to form a battery. Furthermore, if the cells are connected in series, then by Kirchhoff's voltage law, the battery voltage is the sum of the voltages of all the connected cells. By Kirchhoff's current law, the charge capacity of the battery will be same as that of the single cell. On the other hand, if the cells are connected in parallel, then by the same laws battery voltage is equal to the individual cell voltage and charge capacity is sum of the individual charge capacity of the cells [30].

### 2.1.1 Chemical Properties of Battery

The battery cell is composed of electrodes - positive and negative, the elecrolyte and the separator as shown in Fig. 2.1. In traditional batteries, during the discharge, the negative electrode gives up electrons to the external circuit, which causes *oxidation*, subsequently making the electrode increasingly positive. Conversely, during charging, the negative electrode accepts the electrons from the external circuit causing *reduction*, making the electrode more and more negatively charged. This chemical process is therefore called reduction-oxidation or *redox reaction* [30].

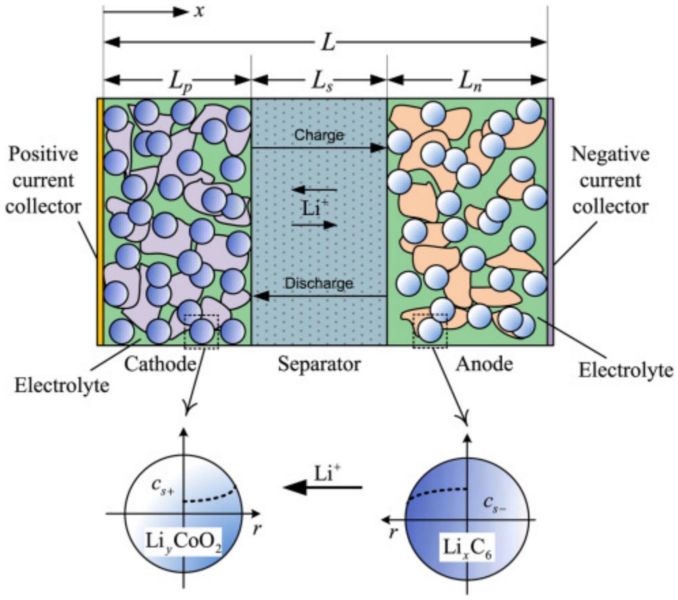



Figure 2.1: Anatomy of Lithium Ion Cell [41].

The Li-ion batteries are usually made of insertion-electrode cells and the process is not a typical chemical reaction. The absorption and expulsion of lithium, to and from electrode, is same as that in a 'sponge'. In Li-ion batteries, the process of absorption of the lithium from the electrolyte at the positive electrode, is called *intercalation*, whereas when the negative electrode releases lithium into electrolyte, then it is called *deintercalation* [30]. As shown in Fig. 2.1, during discharge, li-ion deintercalate from negative electrode into the electrolyte, whereas LiCoO2 particles intercalates at the positive electrode [16]. Henceforth, for the sake of clarity, the discussion will only focus on Li-ion batteries unless specified otherwise.

Wireless sensor devices are usually powered by Li-ion batteries due to their high energy density (100-265 Wh/kg or 250-670 Wh/L) [1]. Thus, they can provide large amounts of current for high-power applications. They also offer longer cycle life than other batteries. Unlike other batteries, these batteries have *almost* no memory effect [40]. *Memory effect*, as shown in Fig. 2.2, is a detrimental process where frequent partial charge/discharge cycles can cause a battery to 'remember' a lower capacity which causes them to hold less charge resulting in wrong estimate of State of Charge (SOC). Additionally, the amount of self-discharge is as low as 1.5-2% per month [1]. The *self-discharge* is the process in which the state of charge of the battery depletes due to internal chemical reactions even when not in use.

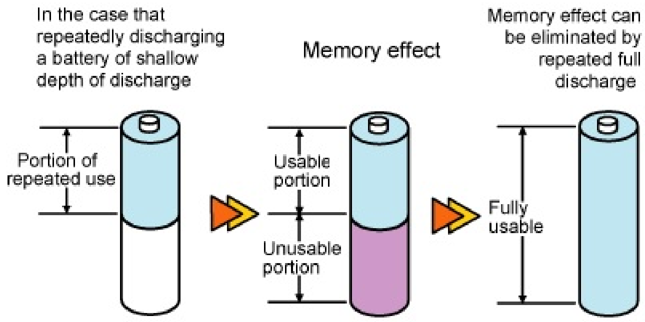



Figure 2.2: Memory effect in rechargeable Ni-Cd Batteries [4].(Note: Lithium-ion batteries do not show memory effect.)

### 2.1.2 Electrical Properties of Battery

Voltage (V) and Capacity (Ampere-hour, Ah) are the two most important properties of a battery. The product of these two values is the amount of energy stored in the battery. Ideally, the voltage of the battery remains constant throughout the discharge and drops to zero at full discharge, and the capacity is same for all the load profiles. Assuming the ideal scenario it is trivial to calculate the *lifetime* of the battery system. In case of constant load, the lifetime (denoted by $L$) is the capacity (denoted by $C$) over load current (denoted by $I$) [21, 30] i.e.

$$L = C/I \tag{2.1}$$

However, in real batteries this is not the case i.e. voltage value drops as the battery discharges and capacity lowers against high load. Thus, according to Peukert's Law the lifetime is no longer capacity over current as shown in Equation. 2.1 but,

$$L = \frac{a}{I^b} \tag{2.2}$$

where a>0 and b>1 are battery constants for *constant load* only. This law does not apply to the batteries which power devices like mobile phones, because for these devices the load varies with time. Such portable devices run different applications with different power requirements, thus categorizing them into time-varying load [34].

It is important to specify that we are dealing with energy-constrained system and it is also worth noting that energy-constrained systems do not always target energy minimization. If an energy-constrained device is powered by a battery of linear nature, then the energy minimization would be a valid design goal for such a system. This implies that in such a case energy minimization will directly impact battery life [43]. However, in real batteries the capacity is **non-linear** as discussed above and therefore battery lifetime is dependent on *current discharge* profile.

The current discharge profile can be measured in terms of C-rate. The C-rate is a measure of the rate at which a battery is being discharged or charged. For example, if the battery capacity is 1C, then that battery when fully charged should provide 1A for one hour. The same battery when discharged at 0.5C should provide 500mA for two hours, and when discharged at 2C it delivers 2A for 30 minutes [11]. It is often advisable to discharge or charge the battery at its rated capacity, because if a current of greater magnitude than the rated capacity of the battery is discharged, then the *efficiency* of the battery decreases i.e. the battery lifetime decreases. This effect is termed as the *Rate Capacity Effect* [24]. The efficiency of the battery is defined as ratio of the delivered energy and the energy stored in the battery.

Furthermore, if a battery is discharged for short time intervals followed by idle periods then the delivered energy improves significantly. For example, in sensors active states interleaved between idle states may help improve the energy output. During the idle periods, also called Relaxation Times, the battery can partially recover the capacity lost in previous discharges. This is termed as the *Recovery Effect* [24]. Rate Capacity Effect and Recovery Effect, together determine the amount of energy that can be extracted from a battery, and consequently its lifetime.

Due to this non-linearity of Li-ion batteries, the goal for these energy-constrained systems, is battery lifetime extension, which is separate from energy minimization [43]. Measurement of remaining capacity or remaining useful lifetime will help in implementing energy aware designs focusing on battery lifetime extension. Battery remaining lifetime is an important battery characteristic which can be measured using various State of Charge estimation techniques. These SOC estimation techniques are critical features of battery management systems (BMS) explained after few paragraphs.

### Degradation of battery life

The re-usability of wireless devices are limited by the lifetime of their batteries. The lifetime and performance of rechargeable batteries deteriorate with time and usage due to irreversible chemical reactions. The deterioration causes loss of useful energy and power. This is called battery *ageing*. There are two types of ageing: calendar ageing and cycle ageing. The cycle ageing occurs due to the charge and discharge cycling of the battery, while the calendar ageing occurs due to all the activities except cycling e.g. storage. Furthermore, the combined effect of cycle aging and calendar ageing is much more complicated topic for analysis [36].

The reason of calendar aging is the formation of **solid electrolyte interphase** (SEI) on the surface of anode as well as cathode. SEI is highly resistant layer which has a low electrical conductivity and high permeability for li-ions. Similarly, the reason for cycle ageing is lithium plating. **Lithium plating** takes place when the li-ions of the electrolyte get reduced to lithium metal at the surface of anode [30].

Alternatively, the lifetime of a battery powered device also depends on several external factors. The external factors are storage time (self-discharge), high temperatures, broad SOC operation ranges, and strenuous load profiles accelerate cell ageing [36].

### 2.1.3 Battery Management Systems

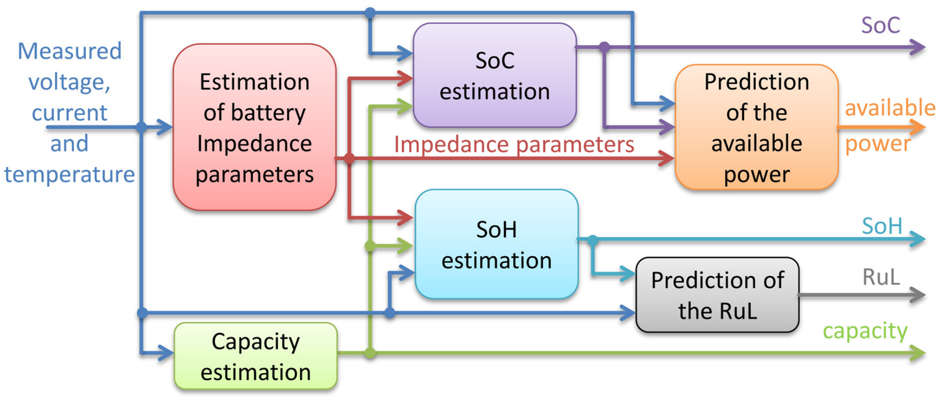



Figure 2.3: Internal process and flow of a typical Battery Monitoring System [46].

From the discussion so far, it has been shown that the battery exhibits complex behaviour due to the non-linear nature which changes as the internal and external conditions change. The complexity further increases over a period of lifetime of the battery as the ageing takes place. These factors make the monitoring of the battery very complicated process. Therefore, Battery Management Systems (BMS) are used predominantly in electric vehicles and smart grids. However, the use of BMSs is also expanding to portable applications and manufacturers are developing integrated circuits which carry out operations equivalent to BMSs in low energy and low current devices [27]. BMS is an integrated circuit with battery management specific algorithms which perform useful tasks as shown in Fig. 2.3. They play an important role in making the battery utilization as safe, reliable and efficient as possible. Firstly, they are used to control operational conditions inside the battery to prolong its life. Secondly, they are used to estimate the State of Health (SOH) and State of Charge (SOC) of the battery for the efficient energy management. BMS controls the charging and discharging as well as keeps in check the battery voltage and current to maintain safety and prolong battery life [46].

#### 2.1.3.1 Fuel Gauges

Batteries which are used in portable and critical applications like medical or military devices are often replaced too soon without testing for their remaining useful capacity. The decision is almost always based on the date stamp or the cycle counts, which does not take the usage into account. Data shows that at times batteries of medical defibrillators with 90% of the remaining capacity get discarded due to the stamped expiry date [11]. This policy of designing a product such that the expiry date ends before the end of useful life is called *planned obsolescence*. The planned obsolescence is a strain on the environment because it causes waste of useful capacity present in the battery. However, it is important to note that 50% of the medical device related problems reported in US are related to the batteries [11]. Therefore, manufacturing industry chooses planned obsolescence costs over troubleshooting costs. This situation arises because it is difficult to test the batteries for their capacities, especially during operation [35]. To counter this, many portable devices and batteries are aided with hardware-based solutions like fuel gauges. However, fuel gauges display the battery SOC (State of Charge) and not the battery capacity and therefore, giving wrong estimation to the user. For example, a battery with half the capacity will still show 100% SOC. Thus, instead of working for 'n' number hours(starting at full capacity), the device will only run for half the amount of time, despite showing fully charged in fuel gauge [11].

#### 2.1.3.2 SOC Estimation

A leading State of Charge indicator of the battery is its *Capacity* which is defined as the ability to store energy. SOC is defined as the percentage of residual capacity ($C_r$) of the battery and the total battery capacity ($C_{bat}$) when it is fully charged, $SOC = \frac{C_r}{C_{bat}} * 100\%$. A li-ion battery offers better capacity when it is new and declines immediately after, however the decline is very slow.

*Discharge test* is the most reliable SOC estimation technique which involves series of charge and discharge cycles. This technique is time consuming and renders the system useless during cycling making it unpopular choice for online SOC estimation [29]. The OCV-SOC method utilises the OCV and SOC linear relationship by measuring OCV values. It is quite common for applications where long rest periods are interleaved with active periods. The main disadvantage is the long time required for the stabilization of the battery dynamics after which the cell terminal voltage matches the OCV. The other disadvantage is the dependence of the cell terminal voltage on the factors like temperature or hysteresis effect [29]. The hysteresis voltage is the difference between the cell terminal voltage and OCV when the cell is left to rest after a charge or a discharge. In ideal situation, the cell terminal voltage must converge into OCV [30].

*Coulomb Counting* is one of the most widely used method due to its simplicity. The accuracy of this method relies on precise measurement of battery charge and discharge current and unambiguous estimation of initial SOC(denoted by $SOC_0$). The following equation can be used to calculate the remaining capacity or SOC where $C_N$ is rated battery capacity and $I_{batt}$, $I_{loss}$ are the battery current and current consumed by loss reactions [29].

$$SOC = SOC_0 + 1C_N \int_{t_0}^{t} I_{batt} - I_{loss} \, d\tau \tag{1}$$

Piller et al. [29] outlined a comparison between various SOC estimation techniques popular in literature. Table A.1 categorically presents the comparison.

## 2.2 Battery Models

In this section, we will discuss the various ways to model the real battery characteristics to measure SOC and battery lifetime. These battery models can be used to study and predict the non-linear discharge behaviour under various load profiles while avoiding prototyping and temporal costs for each alternative.

Battery characteristics resembles that of a living organism which cannot be measured; only estimated by diagnostics similar to a doctor examining a patient [11]. Battery models helps in modelling battery behaviour and its characteristics for the ease of studying and building battery management systems, which further helps in determining remaining useful lifetime, delivered capacity and other important battery parameters. The State of Health of the battery can be determined by measuring the capacity, internal resistance and self-discharge [21]. There is very little work done for the development of lightweight rechargeable battery models that can be built on a wireless network nodes [25]. This motivates us to study and execute battery models that can run on the WSN nodes.

### 2.2.1 Electrochemical models

Electrochemical models are most accurate but computationally intensive and difficult to configure [21]. They take into account the chemical processes and the structural properties of the battery. In comparison to analytical models, a large number of parameters such as electrode geometrics, concentration of the electrolyte, diffusion coefficients, reaction rate constants are required to model electrochemical behaviour of the battery. These parameter values are used to construct a set of battery specific partial differential equations (PDE) [14, 21]. Such models are not applicable for high level battery simulation because of their computational intensity. However, by using spatial and temporal discretization the non-linear PDEs can be converted to coupled nonlinear algebraic equations which reduces the complexity and improves usability [47]. Electrochemical models are used for determining dynamic behaviour of the battery rather than the SOC

### 2.2.2 Analytical Models

Analytical models are high level abstraction of the electrochemical model mentioned above, which ignores the dependence on chemical reactions [26]. It has fewer differential equations and therefore easy on complexity. One of the highly accurate analytical model is KiBaM [26] which demonstrates battery charge and discharge processes using two-tank analogy as shown in Fig. 2.4. The available charge tank supplies power to the device in the form of current $I$ over a period of time $t$. The bound charge tank stores and supplies the charge to the available charge tank through a valve at a rate $k'$. $k'$ signifies the rate of diffusion or chemical reaction and this diffusion takes place when the height $h_2$ is greater than $h_1$. Battery lifetime can be calculated from this model using constants like maximum capacity of the battery, diffusion constant, fractional capacity stored in available charge tank and few other parameters as shown in the Fig. 2.4. Analytical models can estimate the SOC and battery lifetime efficiently if a large set of varying load profiles is given as input for modelling [21]. The delivered charge calculated from the battery model depends on the battery parameters, whereas the battery parameters differ even for batteries with same shapes and sizes. Therefore, a large number of varying load profiles are required to stabilize the input data [21].

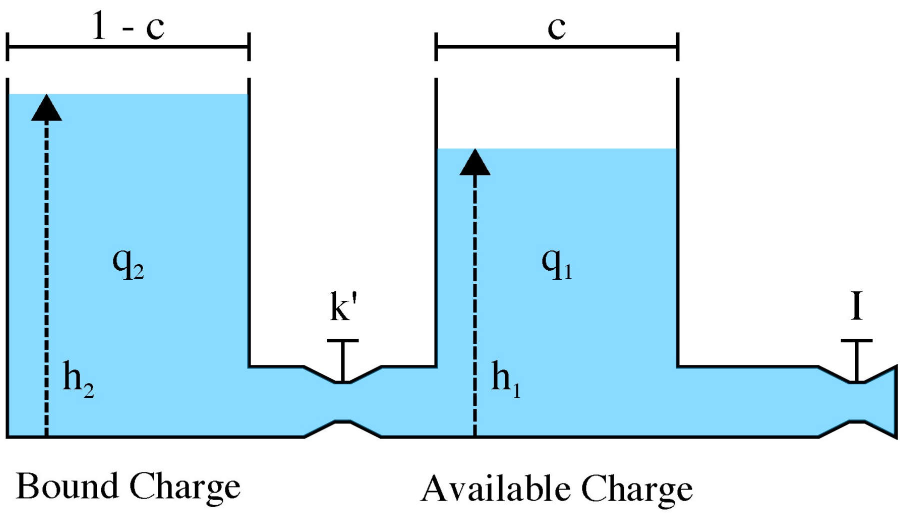



Figure 2.4: KiBaM battery model [38].

### 2.2.3 Equivalent Circuit Models

Equivalent Circuit Model (ECM) uses electrical circuits to represent the electrochemical physics of the battery. The model estimates the dynamic current voltage (I-V) characteristics efficiently. ECM can be easily combined with SOC estimation methods like Coulomb Counting or with an OCV-SOC correlation for periodic recalibration during rest [17]. The structure of the electrical model i.e. number of RC component in the model corresponds to the fitness of the simulated curve and curve obtained from the experimental data. In order to find better fit the number of RC circuit may increase, thereby increasing accuracy. However, it will result in increase of the computational complexity of the model, as a result computational overhead increases and the numerical stability decreases [48]. The computational overhead makes the model unsuitable for embedded applications. Therefore, it is important to find a high fidelity model which simulates at nominal computational cost with adequate complexity. The least complex electrical circuit battery model is first-order RC equivalent circuit as shown in Fig. 2.5.

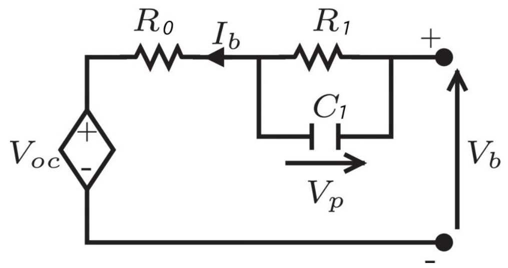



Figure 2.5: Single RC Equivalent Circuit [12].

Here, the open circuit voltage is denoted by $V_{OC}$. It is the controllable voltage of the li-ion battery which usually varies non-linearly with SOC. The ohmic resistance describes the electrolyte resistance and connection resistance of the battery and is denoted by $R_0$, $R_1$ is the polarization resistance, $C_1$ is polarization capacitance, $I_b$ is the current flowing through the load which can be directly measured using a current sensor, and $V_b$ is the terminal voltage of the battery which can be directly measured using a voltage sensor. The parallel RC network describes the non-linear polarization response of the li-ion battery. Departure of the cell terminal voltage away from open-circuit voltage due to a passage of current through the cell is known as *Polarization* [30]. $I_b$ is positive for discharging and negative for charging [49].

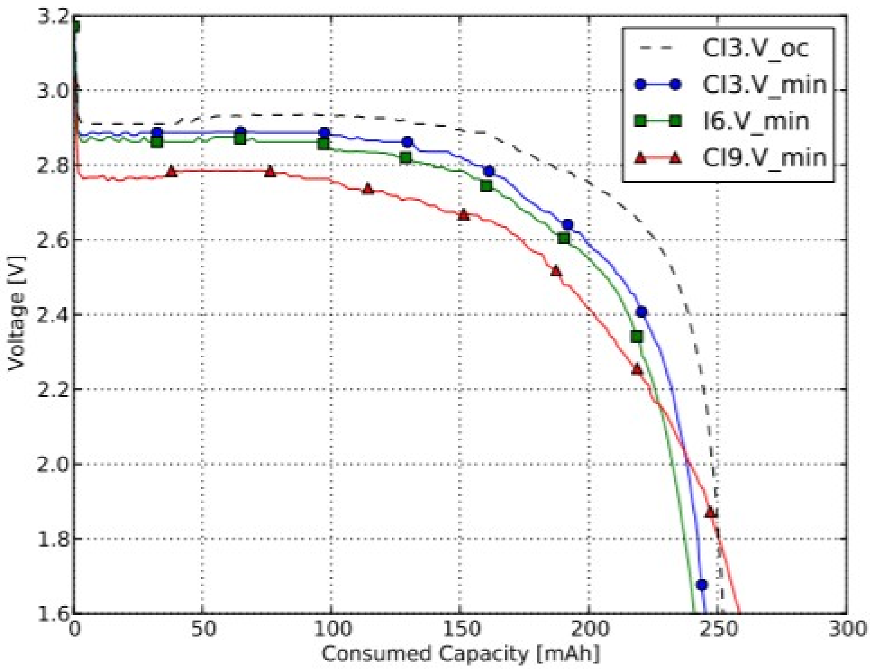
As an implementation of the equivalent circuit model, a hybrid battery model for WSNs [39] is described as follows. This model comprises of a Thevenin's circuit which is a sequence of resistance and capacitance; it models the transient response of the battery to the load. It also comprises of the KiBaM SOC component which models the non-linear behaviour of the open circuit voltage of the battery as the function of its state of charge. These two components are linked by the voltage controlled voltage source and a current controlled current source. This model successfully captures the rate capacity effect, however it is not useful when low current is passed for different duration in order to capture recovery effects.

Rohner et al. [39] measured capacity of the battery in WSN nodes using different load profiles. They developed an automated test bed for this purpose. Their method utilizes different load profiles (CI.3, I.6, CI.9 shown in Table 2.1) to capture the non-linear properties of the battery i.e. rate capacity effect and recovery effect. In Fig. 2.6 b, the Voltage-Capacity curves from

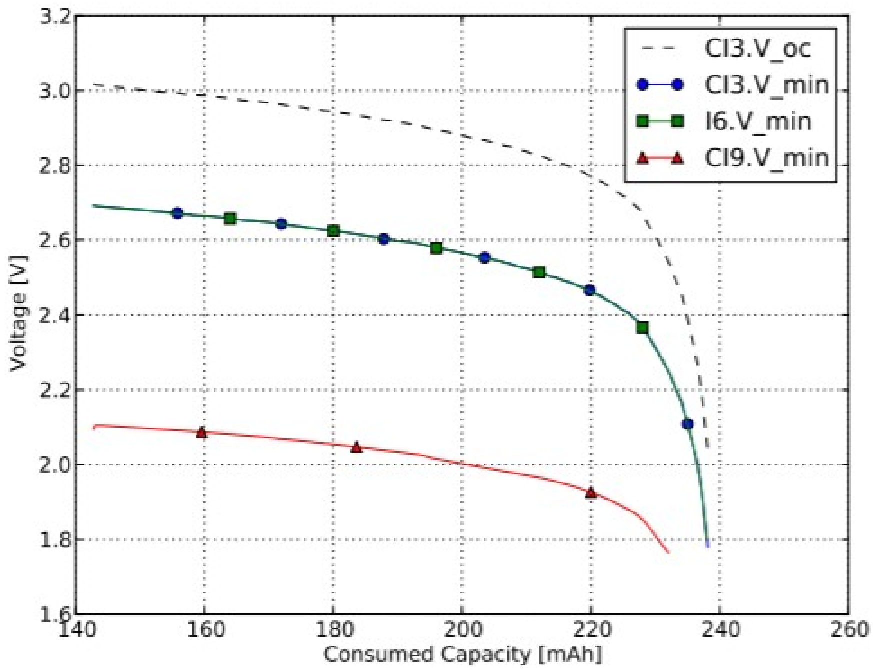
CI.3 and CI.9 shows rate capacity effect i.e. when higher discharge current is applied, the capacity reduces. The CI.9 curve shows that the cut-off voltage is attained earlier when high current is applied for shorter duration. The Voltage-Capacity curves from CI.3 and I.6 in Fig. 2.6 a, gives the recovery effect i.e. relaxation time improves the capacity.

| name | note | load | duration | period | duty cycle | avg. current |
|---|---|---|---|---|---|---|
| CI.3 | low current short period | 750 $\Omega$ (∼4mA) | 15 ms | 200 ms | 7.5% | 300 $\mu A$ |
| I.6 | low current long period | 750 $\Omega$ (∼4mA) | **150 ms** | **2.0 s** | 7.5% | 300 $\mu A$ |
| CI.9 | high current short period | 120 $\Omega$ (∼**25mA**) | 2.4 ms | 200 ms | 1.2% | 300 $\mu A$ |

Table 2.1: Battery load profiles [39].




(a) Battery discharge curve using experimental data from testbed used in experiments shows that a shorter load duration is more battery efficient.




(b) Battery discharge curve using electrochemical modelling, rate capacity effect is visible because CI9 reached cut-off voltage much earlier.

Figure 2.6: Battery discharge curves [39].

# Chapter 3

# Environment

This chapter will briefly describe the energy constrained WSN system which this thesis examines. Then, it will discuss energy profiling technique to gauge energy consumed in various subsystems of WSN, followed by a hint on how modelling can be used to build energy aware systems. Furthermore, *User* is the most important part of environment in which the device and battery operates. Therefore, towards the end, a brief discussion on the impact of user's interaction with the device on battery lifetime.

Real time battery operated systems are often energy constrained owing to the finite lifetime of the batteries. Applications like medical monitoring systems and remote sensors are often found trading off between performance and battery life. Moreover, users demand a high number of functionalities from these systems which adversely impacts the battery life. In order to find the balance between them, the developers try to improve the power efficiency for example, by lowering the clock rate of the CPU. However, it should be noted that a power-efficient device may not always be energy-efficient. Energy is the product of power and time period. The aggressive decrease in the clock rate may improve the power efficiency however, this would not ensure the system's energy efficiency. The decreased clock rate may decrease the performance to an extent such that energy consumption of the system will increase. It is therefore challenging for the developers to find a balance between performance, user needs and system architectural design which supports longer battery life.

The wearable monitoring system is a patient monitoring platform, where the physiological data being monitored is acquired by wearable, battery operated sensors (Analog Front End) and is transmitted over body area network (BAN) to monitoring hub device. The system consists of various subsystems namely wearable sensors, processing and viewing devices, all connected together through different networks. The wearable monitoring system is illustrated in the Fig. 3.1.

The sensor node architecture is divided into four subsystem components:

- sensing subsystem which consists of Analog front end (AFE) for data collection;
- processing subsystem to process the collected data;
- communication subsystem to transfer data over radio;
- battery unit for power supply (PMU).

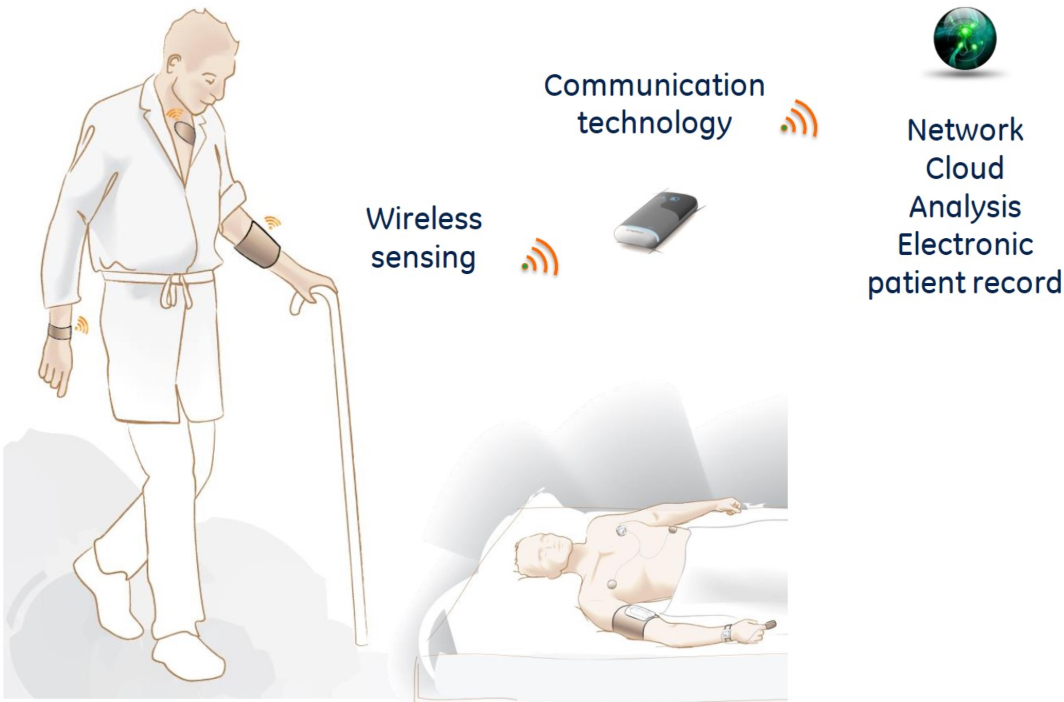



Figure 3.1: Wearable Patient Monitoring [13].

The sensing devices are connected to the sensor batteries, and they both are running on their own microcontroller units (MCU). The embedded sensing system runs on top of real time operating system (RTOS). The sensing device mainly performs sending and receiving of data over peripheral interfaces, as well as pre-processing of raw signals to some extent. All these processes are powered by the attached sensor battery. In order to keep the device functional for longer duration, it is necessary to minimize the battery consumption when the processes are not in use.

Many factors contribute towards poor battery life of patient monitoring devices. Firstly, the WLAN and Body Area Network (BAN) are power hungry features and they contribute towards most of the battery drain. Secondly, the background computation is always on and therefore responsible for battery consumption. Thirdly, it being a medical monitoring device, the requirement is to monitor constantly. The communication, computation and reporting of the vital medical data is responsible for the battery drain. The sensor and sensor battery setup is illustrated in Fig. 3.2.

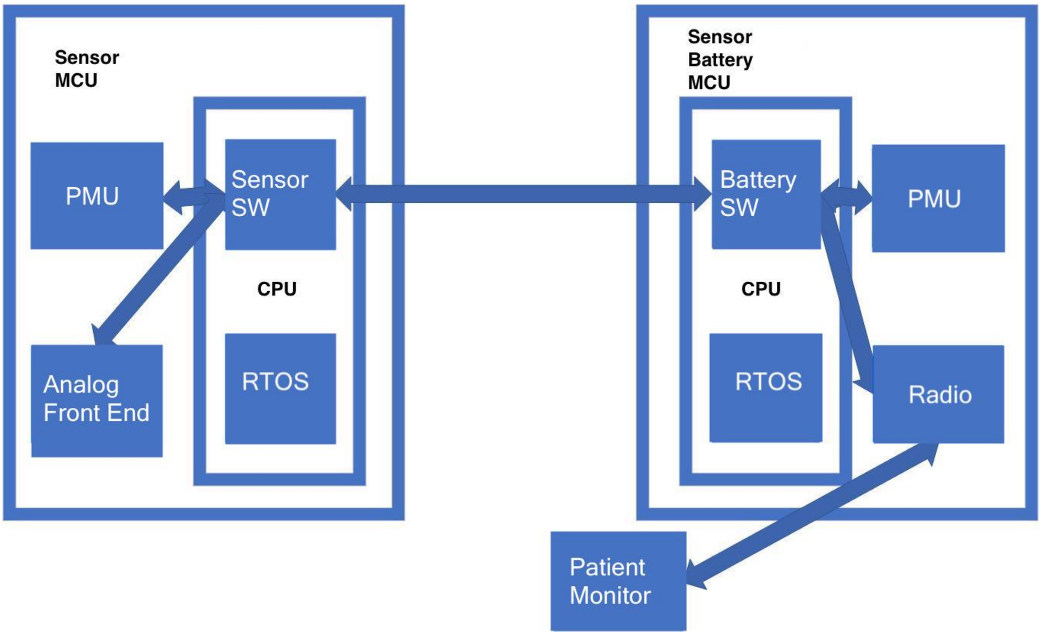



Figure 3.2: Basic work flow between Sensor and Sensor Battery.

## 3.1 Wireless Sensor Subsystem and its Energy consumption

As stated previously, wireless sensor devices are energy constrained applications and their energy consumption has been the focus point in various WSN studies. Besides energy constraints (owing to the limited battery power), limited processing capability and storage capacity also play a huge role in determining the complexity of the task. Therefore, it is a challenging opportunity to design and implement such applications where energy consumption of the node is optimized. Higher optimization can be achieved by reducing the power consumption of the device. The lowering of energy consumption in nodes directly impacts the network lifetime and vice versa. The lifetime of the wireless sensor networks can be maximised by 1) coordinating duty cycles (sleep/active modes) of the sensor nodes of the network, or by switching the nodes on/off on the basis of requirement 2) balancing the energy load between various nodes, given that the nodes nearer to the sink are more loaded as compared to the nodes that are far away. Routing techniques like *equiproportional* and *shortest-path* are conventionally used in energy balancing solutions [22]. As the name suggests, equiproportional technique involves distributing the load equally among the upstream neighbouring nodes, while shortest-path is the least costly route in terms of energy consumption from any node towards the base station. This discussion was made to point out that there are various ways to reduce energy consumption in WSN and it is therefore often a trade off between them, when it comes to achieve energy efficiency.

Furthermore, in the context of wireless sensor devices, *energy profiling* of various components of wireless sensor nodes helps in designing energy efficient sensing systems [10]. Such profiling helps in classifying the main energy consumers within the system and enables us to take necessary action to reduce their consumption. However, energy profiling of the components is a challenging task because energy profile depends on the individual and average power of the components. The amount of load current and power use during normal operation vary significantly, making it hard to accurately determine average power consumption of the components. *Microbenchmarking* [23] approach can help in mapping operation time and load current for an individual component giving power consumption per component, simultaneously, using oscilloscope or ammeter to determine the average power.

Generally, communication subsystem consumes far more energy than the processing subsystem [32]. The validity of this statement can be proved by applying *Microbenchmarking* technique on patient monitoring system. Microbenchmarking is a software that is used to measure the performance of individual subroutines of a more complex software or lower level hardware components such CPU [31]. Once it is established that a component is responsible for maximum power consumption, it will be easier to do complete profiling of that component. For the complete profiling of the energy consumption of the component, it is important to know *when* is the power most utilised i.e., is it during start-up or during normal operation or is it during longer period of operation.

These estimated energy profiles can be then utilised to further estimate the battery lifetime using analytical model in wireless sensor networks. This is a challenging task because firstly, the implementation of complex analytical models on low-capacity hardware platforms of the sensor network is not easy. Alves [8] states that low-capacity hardware platforms are limited by low processing capability and memory constraints. Additionally, the high accuracy required to represent low varying analog values hinder the usefulness of analytical model in these low-capacity hardware platforms. Secondly, the execution of complicated analytical models by real-world energy starved nodes will impact its energy consumption, and therefore, the increase in energy consumption to estimate the network lifetime may reduce the lifetime of the network itself [8]. A similar approach is discussed by Lahiri et al. [24] as Battery-Aware Task Scheduling. This approach is presented as an implementation of the battery model in Chapter 6.

## 3.2 User Interaction with handheld device and batteries

It is pointed out earlier in the chapter that there are several factors like WLAN, BAN and uninterrupted background computation which contribute to the battery drain. In addition to those, users interaction with the handheld devices also determines the battery lifetime. We know that more the number of charge/discharge cycles, the less is battery capacity. Unnecessary charging leads to increased number of charge/discharge cycles. According to Banerjee et al. [9], users charge their mobile phones as and when they find charging opportunity, rather than wait for the low battery signal flashing. The users also often ignore the remaining battery capacity before putting for charging, which causes waste of useful energy. Extrapolating this behaviour to patient monitoring devices, we assume that this abuse of battery will result in early battery ageing. In order to avoid battery ageing due to mishandling, a good understanding of resources that are demanded by users is required. It is also required to understand the use of resources and applications in the system. Every energy efficient device designer must be aware of how and when the energy is wasted by the user [44].

# Chapter 4

# Methods and Implementation

In this chapter we will first discuss and compare various battery modelling techniques which are available in literature and are suitable for WSN applications. This will help the reader to compare the advantages and disadvantages of some applied techniques specifically in low power wireless devices. Then, the highlight on the main elements of the method used in this thesis work. The battery modelling, testing and validation techniques will be presented along with the data obtained for the purpose of these techniques.

For this study, Equivalent circuit model is chosen because of the simplicity and ease of use. The data gathered from Pulse Current Discharge will be used to create Lookup tables. These Lookup tables will be then used for Parameter Estimation, Extraction and Optimisation in Equivalent Circuit Modelling.

## Literature Review

Rodrigues et al. [38] proposed a computationally inexpensive method known as T-KiBaM (Temperature-Dependant Kinetic Battery Model) to analytically model the batteries of low power, small memory MCUs, typical of WSN nodes. The model uses discharge current profiles and other inputs like temperature and voltage. The basis of the proposed model is high accuracy analytical battery model called KiBaM [38] described in Section 2.2.2. The main advantage is that the model is suitable for low power WSN sensor nodes and is independent of the used hardware, because it uses discharge profile as an input. It is able to accurately estimate lifetime and voltage behaviour of Ni-MH batteries based on energy profiles and not on real sensor network. However, the study presented in their work does not show any results for Li-ion batteries which have higher energy density compared to Ni-MH and are more sensitive to temperature. The model is not tested with real time data which is another limitation. However, these limitations were overcome later by the same team [37]. They experimentally validated the model against the real operational conditions with varying temperatures for lithium ion batteries.

Doyle et al. [14] modelled one-dimensional transport of the lithium ion from the lithium anode through the polymer separator into the composite cathode. They reduced complexity by overlooking the film formation at the lithium/polymer interface and changes in the volume due to chemical reaction. The parameters of *electrochemical model* simulation vary for different battery chemistry, battery type and its manufacturer. The simulations often run between two days and four weeks each, depending on the number of load events to be simulated. Another disadvantage is the difficulty in integrating the mathematical structure of the simulation with the common discrete-event WSN simulators. The discrete nature of the WSN is due to the fact that transmitting a frame involves a sequence of transitions between backoff, listening, and transmitting states. However, Dualfoil is a model freely available on internet, based on the principles presented by Doyle et al. [14]. It is a Fortran program to model and simulate the lithium-ion battery behaviour based on different load profiles. Because of the accuracy and complexity of the model, it has been used as a tool to compare other models rather than actual lifetime estimation model.

Researchers have developed various electrical circuit models to capture the dynamic characteristics of Lithium-ion batteries. PSPICE macromodel [15] uses separate loops to estimate first order effects like state of charge and capacity. The measurement data sheets from the manufacturer and look up tables are used for coupling the parameters present in various loops. The model is inaccurate because the output of charge and discharge cycles show voltage curve reciprocal to each other which does not support laws of thermodynamics. The real batteries have irreversible chemical reactions; the dissipated losses make the battery efficiency $< 1$. Thus, the charge and discharge cycles can not give similar curve.

## 4.1 Experimental setup and method used

In this study, the characterization of battery cell is performed using equivalent circuit model prepared by Huria et al. [20]. Due to the unavailability of WSN simulation test bed and limited research time, it was not possible to combine the effects of load profile on the battery model for study purposes. Therefore, the scope of the thesis is limited to the bare battery testing and modelling. As a future enhancement, the study should take place with the help of Network simulator tool NS2 [3]. Nonetheless, in the following text a description of the experimental setup, data collection, model curve fitting and validation of the experiment is presented.

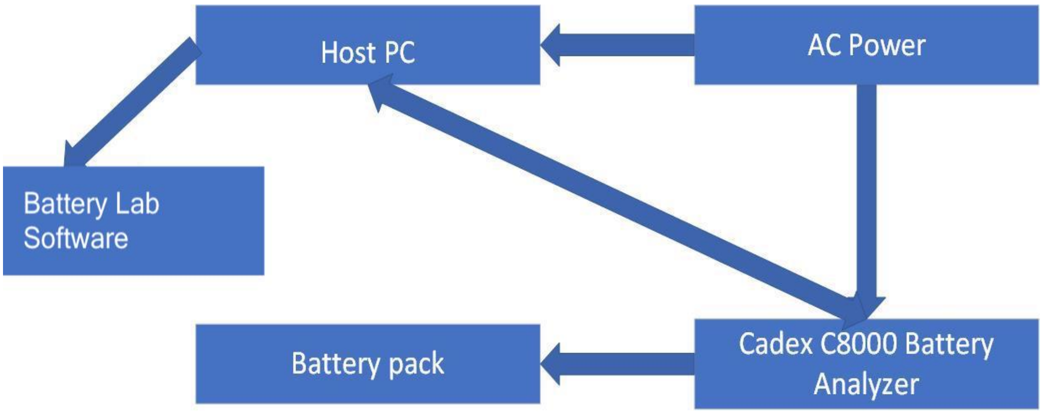



Figure 4.1: Experimental setup.

### 4.1.1 Measurement

#### 4.1.1.1 Cadex C8000 Battery Analyzer

The setup for measurement of the experimental data is shown in Fig. 4.1. The Battery Analyzer System called Cadex C8000 is used to charge and discharge the battery, and measure the important parameters like voltage, current and temperature. The measured data is stored in the BatteryLab Software installed on the host PC. The battery analyzer can be programmed to execute constant current discharge or pulse discharge at various C-rates using BatteryLab software. Similarly, the system is capable of charging the battery to a certain voltage level at user defined C-rates or current value. For the experimental data, the sensor battery packs were cycled at room temperature and the results were collected in Microsoft excel sheets. This measurement data will be further used in modelling and creation of lookup table. The system comes with Power Port cables which are connected to four channels, which is used to simultaneously cycle 4 different batteries.

#### 4.1.1.2 Sensor bare battery pack

The experimental data is collected by cycling bare battery packs which are used in sensor battery devices. These are pack of three circular batteries connected together to power the sensor device. The nominal voltage of the battery pack is 3.7V with nominal capacity of 120 (at 0.2C from 4.2 V to 3.0 V at 20°C).

### 4.1.2 Modelling

The data values collected from the experiments performed on sensor bare batteries using Cadex C8000 are tabulated into Microsoft excel sheets to be used as input for the Battery pack model in MATLAB®, Simulink, Simscape$^{TM}$. The experimental values represent the battery performance at various operating points when the battery pack is subjected to *Pulse discharge current*. The Pulse discharge of C-rate 1C for 6 minutes, followed by 30 minutes of resting period is applied to the battery until it reaches its minimum cut-off voltage i.e. 3.0V. The pulse discharge current is used in this experiment because, it extracts the data which captures the internal dynamics i.e. recovery effects of the battery. The discharge curve shows how the battery recovers during rest period.

#### 4.1.2.1 Equivalent Circuit Model

The model used in this study is based on high fidelity electric circuit non-isothermal lithium cell model developed by Huria et al. [20]. However, the temperature is assumed constant making the model isothermal in nature for this particular study. The battery pack model is based on Thevenin's equivalent circuit model, which will be used to capture the I-V characteristics and transient behaviour of the battery. Thevenin's circuit model represent the resistive and capacitive properties of the battery. This model is the most popular model among the other time-domain models namely Rint, PNGV, and GNL. The reason is that it performs better than other models in terms of measuring polarisation characteristics and estimating with lower error rate. From the Fig. 2.5, the polarisation resistance is represented by $R_1$ while the polarisation capacitance is represented by $C_1$. The ohmic resistance, which is denoted by $R_0$, represents the resistance of the electrolyte and connection of the battery [19].

This model does not characterize self discharge property of the battery because it was not intended to simulate long term behavior due to time constraints. Moreover, lithium batteries have the least amount of self-discharge which is around 2-3% discharge per month. Additionally, this model does not capture cell impedance and assumed that it did not change significantly due to the magnitude of the discharge current [20].

A second-order Thevenin's equivalent circuit model as built in MATLAB Simulink is shown in Fig. 4.2.

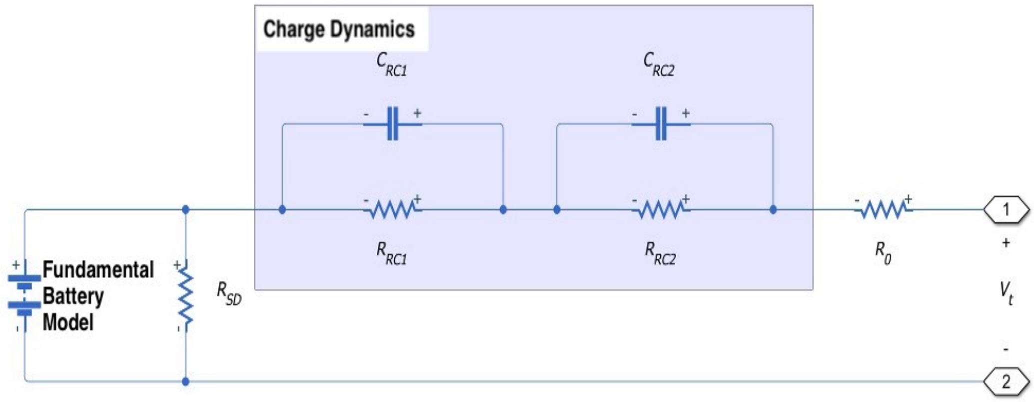



Figure 4.2: The equivalent circuit representing two time-constant dynamics [2].

Here, $R_{RC1}$ is the first polarization resistance and $R_{RC2}$ is the second polarization resistance. $C_{RC1}$ and $C_{RC2}$ are the parallel RC capacitances. The time constant $\tau$ and the R and C values are estimated using the relationship $C=\tau/R$. $\tau$ is specified for each section for example First time constant ($\tau 1$) and Second time constant ($\tau 2$) parameters, respectively. $R_0$ is the Internal resistance parameter.

#### 4.1.2.2 Parameter Extraction and Estimation

The numerical parameter estimation is performed by iteratively simulating discharge profile and comparing it with experimental values. The parameter values of the equivalent circuit model are collected in Lookup tables as dependencies of SOC. A *lookup table* is an array of data that maps input values to output values, thereby approximating a mathematical function [2]. The lookup tables are suitable for such parameter estimation tasks because they are flexible and provide distinct values of each parameter when numerical optimizer is applied on pulse discharge profile. There are two sets of tables for different temperature values; the initial guess table and the final value table. To avoid complexity, the experiments in this paper are conducted at room temperature.

The initial guess lookup table consists of estimated value for each circuit element as a function of SOC using equations from the Fig. 4.3. The table values are calculated using a large set of experimental data. The first set of values serve as the initial guesses and based on these guesses final values are calculated using the optimization algorithm. The parameter estimation therefore becomes optimization problem which consists of set of model parameters, a cost function *F(x)*, optional bounds on parameter values, and optional constraint function *C(x)* which limits the parameters. The optimization algorithm works towards minimizing the cost function (or an estimation error) between the measured battery terminal voltage and the simulated voltage values obtained from ECM. The data is optimized till the point the measured voltage values match exactly to the simulated values and thereby giving the estimated final look up table for each parameter. MATLAB®design optimization tool provides inbuilt cost function namely, Sum Squared Error and Sum Absolute Error for parameter estimation. It can be noted that for better curve fitting, customized cost function executed at command line can be used [2].

For model validation, an independent set of experimental data is required and general simulation is applied to validate the results of the experiment.

## 4.2 Implementation

One of the objective of this work is to replicate the dynamic and non-linear properties of the battery. The model is intended to interact in the same way the battery interacts with the real world. In order to focus on the electrical properties alone the implementation will ignore many battery related important electrochemical properties which depend on the internal chemistry and charge distribution.

### 4.2.1 Model

The comprehensive model is as shown in the figure below. The battery model is built using Thevenin's circuit model in MATLAB using Simulink and SIMSCAPE. This model is derived from the high fidelity electrical model presented by Huria et al. [20] by adjusting some of the parameters to meet low power sensor battery pack requirements.

### 4.2.2 Parameter Extraction using Lookup table

Parameter extraction gets computationally expensive as the number of RC elements increase in the ECM. Extraction is done using lookup tables which contains parameter values as a function of SOC i.e. $E_m$(SOC), $R_0$(SOC),

$C_1$(SOC), $R_1$(SOC),.., $C_n$(SOC), $R_n$(SOC), where $n$ is the number of RC elements. These values are estimated using equations from Kirchoff's law. For this study, the value tables are prepared while assuming constant ambient temperature because the amount of charge/discharge current is too small to cause any significant temperature shift which may impact the model. The temperature is 23°C. The lookup table below contains the initial values of the parameters as derived from the measured data and some initial guess using equations from Fig. 4.3. The instantaneous drop or rise of the voltage ($\Delta V_0$) is equal to the product of current ($\Delta i$) and the series resistance ($R_0$). The capacitance does not contribute to the voltage change because the voltage across capacitor does not change instantly. The value of $R_0$ can be determined by substituting the value of current ($\Delta i$) from the experiment setup and value of voltage ($\Delta V_0$) from the simulation readings [30].

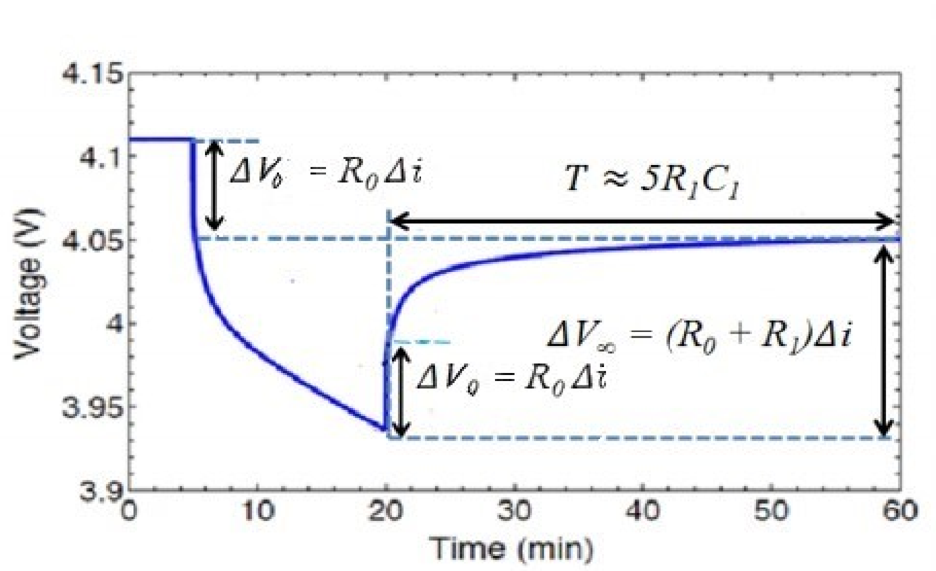



Figure 4.3: Parameter Extraction from Initial Guess Formula [30].

| SOC | Em | R0 | R1 | C1 |
|---|---|---|---|---|
| 100 | 3.4 | 0.01 | 0.0005 | 4000 |
| 90 | 3.49 | 0.01 | 0.0005 | 4000 |
| 80 | 3.5 | 0.01 | 0.0005 | 4000 |
| 70 | 3.55 | 0.01 | 0.0005 | 4000 |
| 60 | 3.65 | 0.01 | 0.0005 | 4000 |
| 50 | 3.7 | 0.01 | 0.0005 | 4000 |
| 40 | 3.8 | 0.01 | 0.0005 | 4000 |
| 30 | 3.9 | 0.01 | 0.0005 | 4000 |
| 20 | 4.0 | 0.01 | 0.0005 | 4000 |
| 10 | 4.1 | 0.01 | 0.0005 | 4000 |

Table 4.1: Initial Guess for parameters using 1 RC component.

The Fig. 4.4 shows the output of the first execution of the model using 1RC component. Table. 4.1 displays the corresponding values. In this figure, the measured data denoted by voltage_exp curve and the simulated data denoted by voltage_sim curve shows mismatched model to the battery behaviour. The aim is to bring the simulated curve and experimental curve closer to each other.

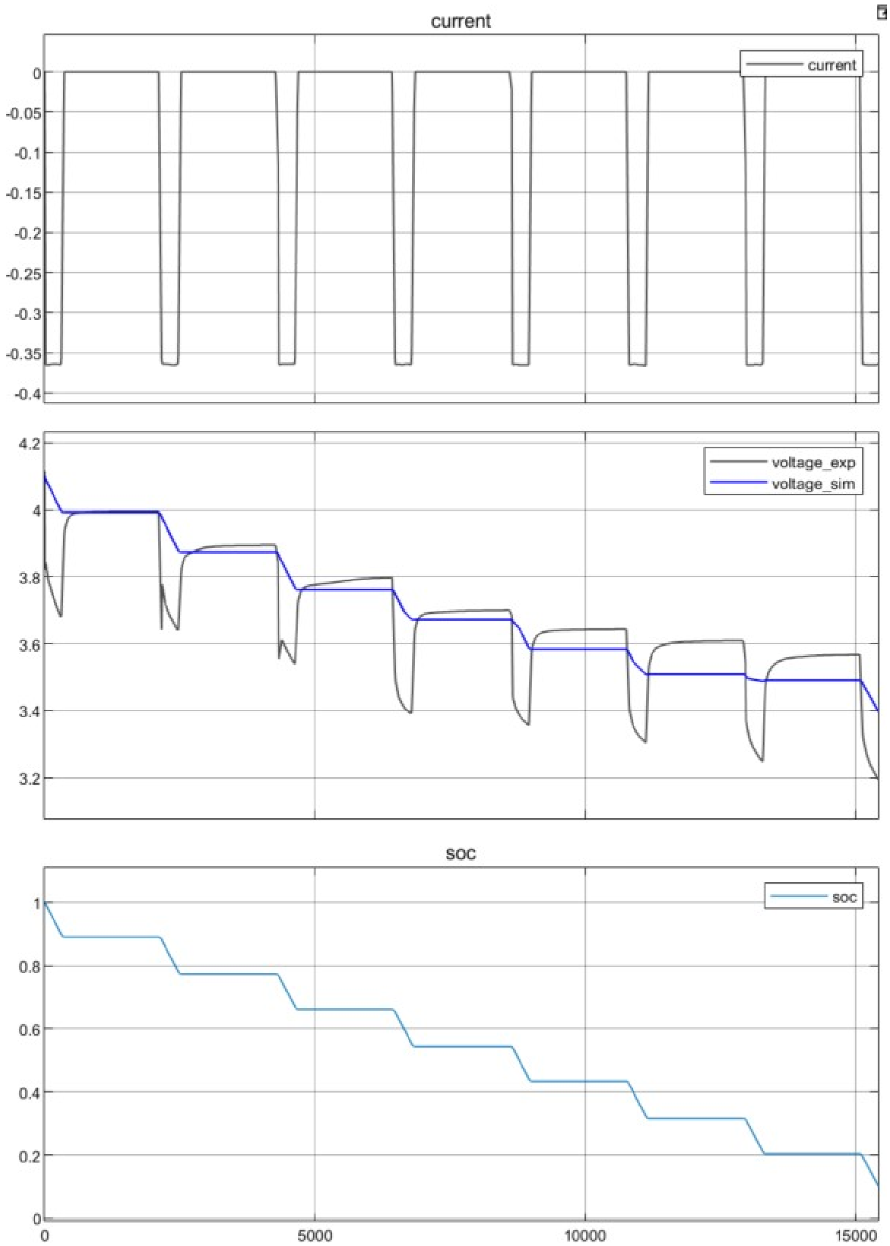



Figure 4.4: Measured and Simulated Curve for Initial Guess.

### 4.2.3 Parameter Estimation

Parameter Estimation is performed using the Simulink Design Optimization Tool which estimates resulting values using measured, time-domain input data [2]. The parameters are analysed and tuned to fit the model to the test data. The process of estimation is carried out either by the estimation code or by using the software estimation tool. In order to use tool, the first step is to load the time-domain input data into the experiment, followed by selecting the parameter with some initial guess values. The values can be optionally limited by the bounds or by the constraint function *C(x)* before the real estimation begins. When the data and parameters are set for the experiment, next step is to select the cost function *F(x)* which in this case is Sum Squared Error,

$$F(x) = \sum_{t=0}^{t_N} [V_{measured} - V_{simulated}]^2 \tag{4.1}$$

N is the number of samples.

The time-base for the experiment is derived from the measured signal data set. If the simulated and measured signal time bases are different, the software evaluates the cost function for the time interval that is common to both. It is also possible to modify the simulation time-base by using time setting in Simulation Options dialog box.

The optimization method selection is based on the nature of the problem. If the model data output needs to track the measured signal data, the problem is a minimization problem, which minimizes cost function *F(x)*. The minimization problem can be solved using the Nonlinear Least Squares method.

If the problem is to minimize the cost function *F(x)* as well as keep the model response within the specified bounds and constraint function *C(x)*, then it is identified as Mixed minimization and feasibility problem. The offered method for such problems is *Gradient Descent*.

If the problem is only to keep the parameters in bound and constraint, then it is classified as Feasibility problem. It does not require to minimize the cost function at all. The bounds and constraint function should be well defined.

The final values for the parameters are derived by running the with 1RC component. Table. 4.2 displays the corresponding output values.

| SOC | Em | R0 | R1 | C1 |
|---|---|---|---|---|
| 100 | 3.4026 | 0.53204 | 0.04218 | 7.285 |
| 90 | 3.5546 | 0.74031 | 0.00039186 | 18857.75 |
| 80 | 3.5981 | 0.77404 | 0.00049022 | 4034.025 |
| 70 | 3.6194 | 0.71919 | 0.0003575 | 5178.405 |
| 60 | 3.6784 | 0.7844 | 0.00068663 | 3177.257 |
| 50 | 3.7104 | 0.83368 | 0.00047102 | 3582.395 |
| 40 | 3.8257 | 0.70109 | 0.00054585 | 3204.030 |
| 30 | 3.9046 | 0.68848 | 0.00049697 | 4205.888 |
| 20 | 3.9966 | 0.84592 | 0.00052351 | 3928.865 |
| 10 | 4.1147 | 0.79061 | 0.00095061 | 2295.158 |

Table 4.2: Final values using 1 RC component.

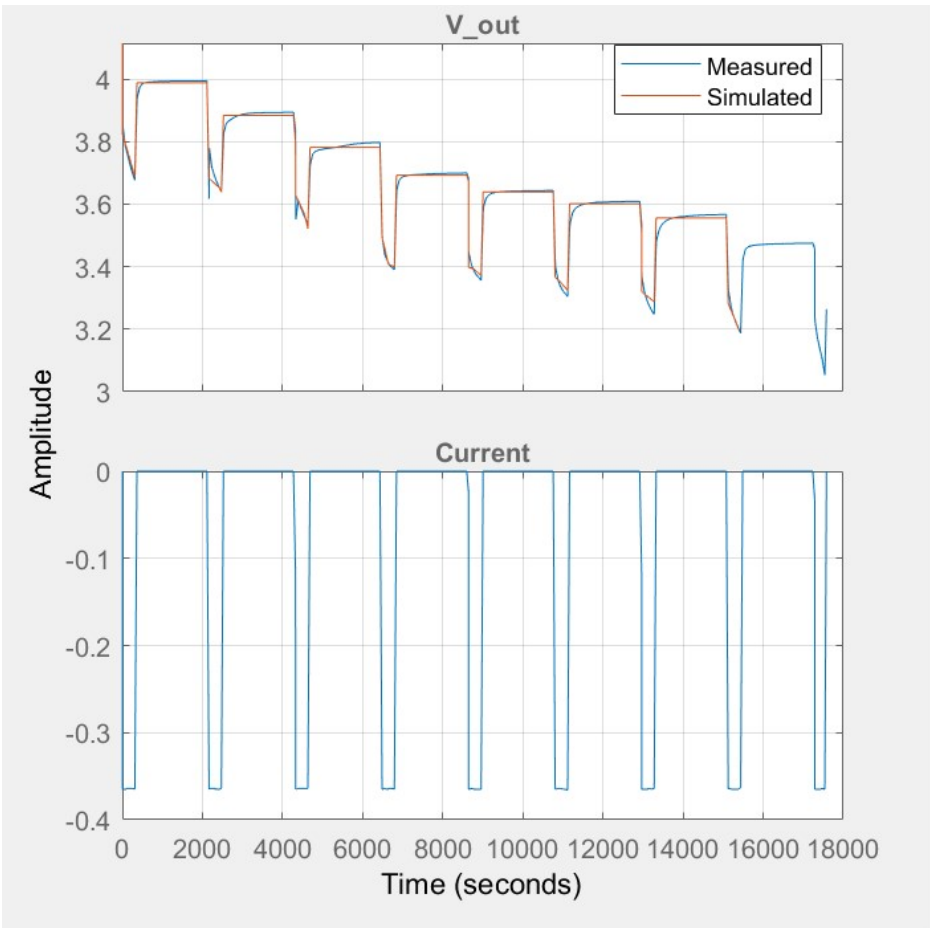



Figure 4.5: Measured and Simulated Curve for Final values using 1RC.

The Fig. 4.5 shows the curve fitting of the measured data against the simulated data. The closer look in Fig. 4.6 clearly shows how the data fits to the curve. The simulated curve followed the measured curve to a great extent, however the edges are showing mismatch.

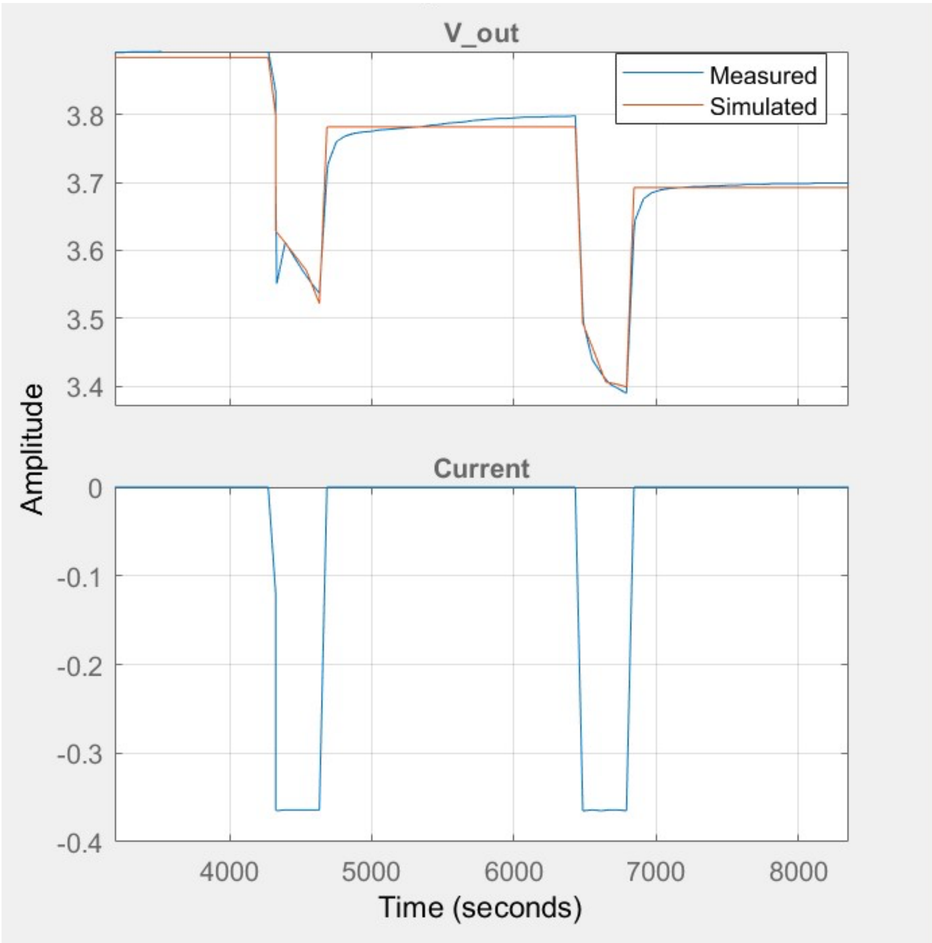



Figure 4.6: Closer look at the Measured and Simulated Curve for Final values using 1RC.

In the final attempt, the values are derived against the model with 2RC component. It is expected that 2RC component model can solve the mismatched curve at the edges and provide more fitting curve with accurate parameter values. This requires the model to be updated with existing values from 1RC component. The Table 4.3 shows the final values using 2RC component model. Fig. 4.7 and Fig. 4.8 shows the curve fitting for 2RC component.

| SOC | Em | R0 | R1 | C1 | R2 | C2 |
|---|---|---|---|---|---|---|
| 100 | 3.4026 | 0.53204 | 0.04218 | 7.285 | 0.0005 | 40000 |
| 90 | 3.4056 | 0.40264 | 0.0005 | 155212 | 0.19313 | 77.197 |
| 80 | 3.5626 | 0.65096 | 0.0005 | 11834.8 | 0.25037 | 116.963 |
| 70 | 3.6067 | 0.68327 | 0.0005 | 17799.6 | 0.21906 | 124.459 |
| 60 | 3.6114 | 0.55551 | 0.0005 | 14494.4 | 0.19525 | 152.113 |
| 50 | 3.7009 | 0.70304 | 0.0005 | 1189.6 | 0.1762 | 41.454 |
| 40 | 3.6927 | 0.79089 | 0.0005 | 42076 | 0.007873 | 1515.051 |
| 30 | 3.8344 | 0.72115 | 0.0005 | 3963.36 | 0.0072697 | 25294.029 |
| 20 | 3.909 | 0.64061 | 0.0005 | 5970.4 | 0.01071 | 6876.751 |
| 10 | 4.0004 | 0.81823 | 0.0005 | 1147.2 | 0.14105 | 188.912 |
| 0 | 4.1122 | 0.778 | 0.0005 | 4531.6 | 0.013661 | 1644.828 |

Table 4.3: Final values of the parameters using 2 RC component.

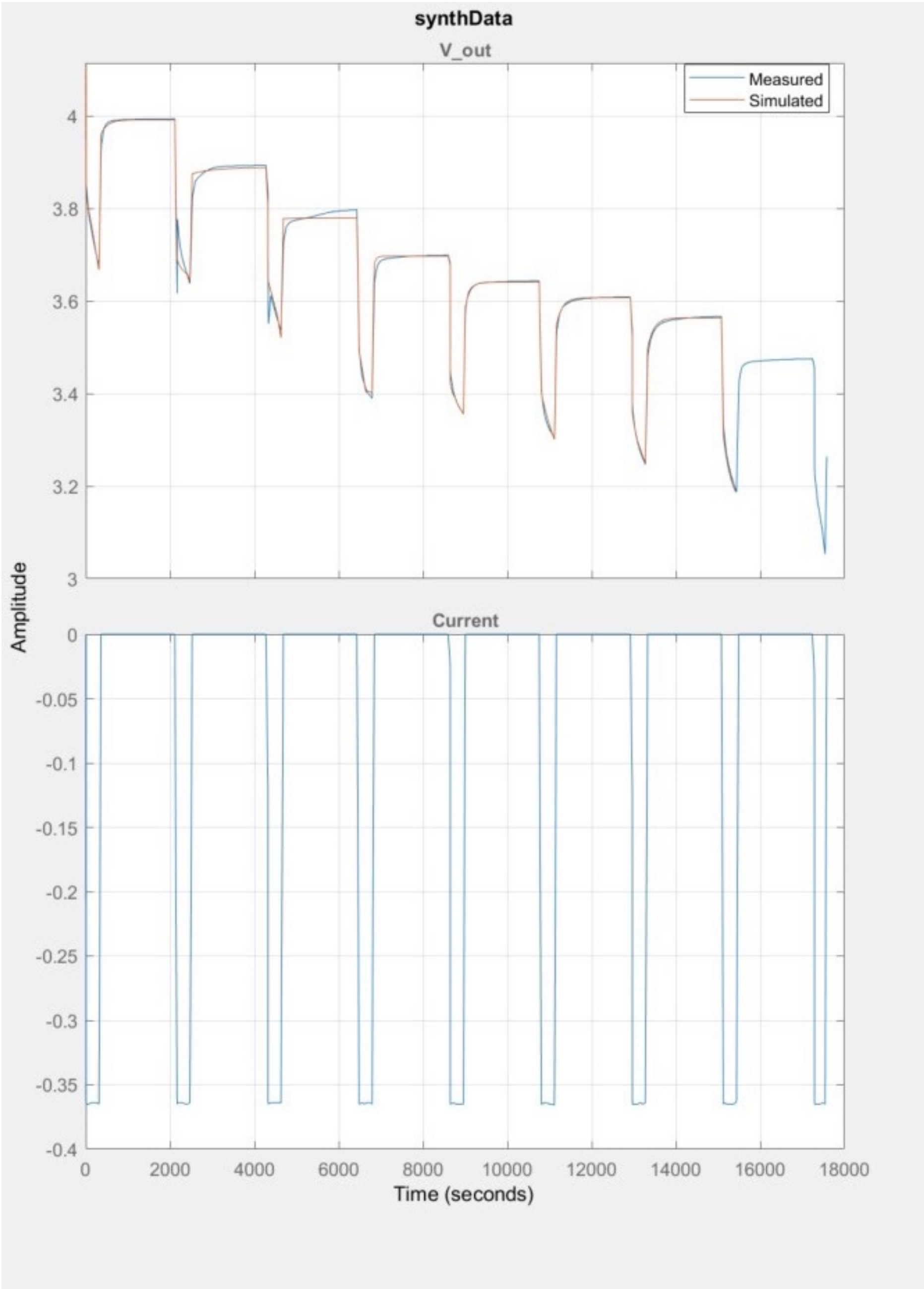



Figure 4.7: Measured and Simulated Curve for Final values using 2RC.

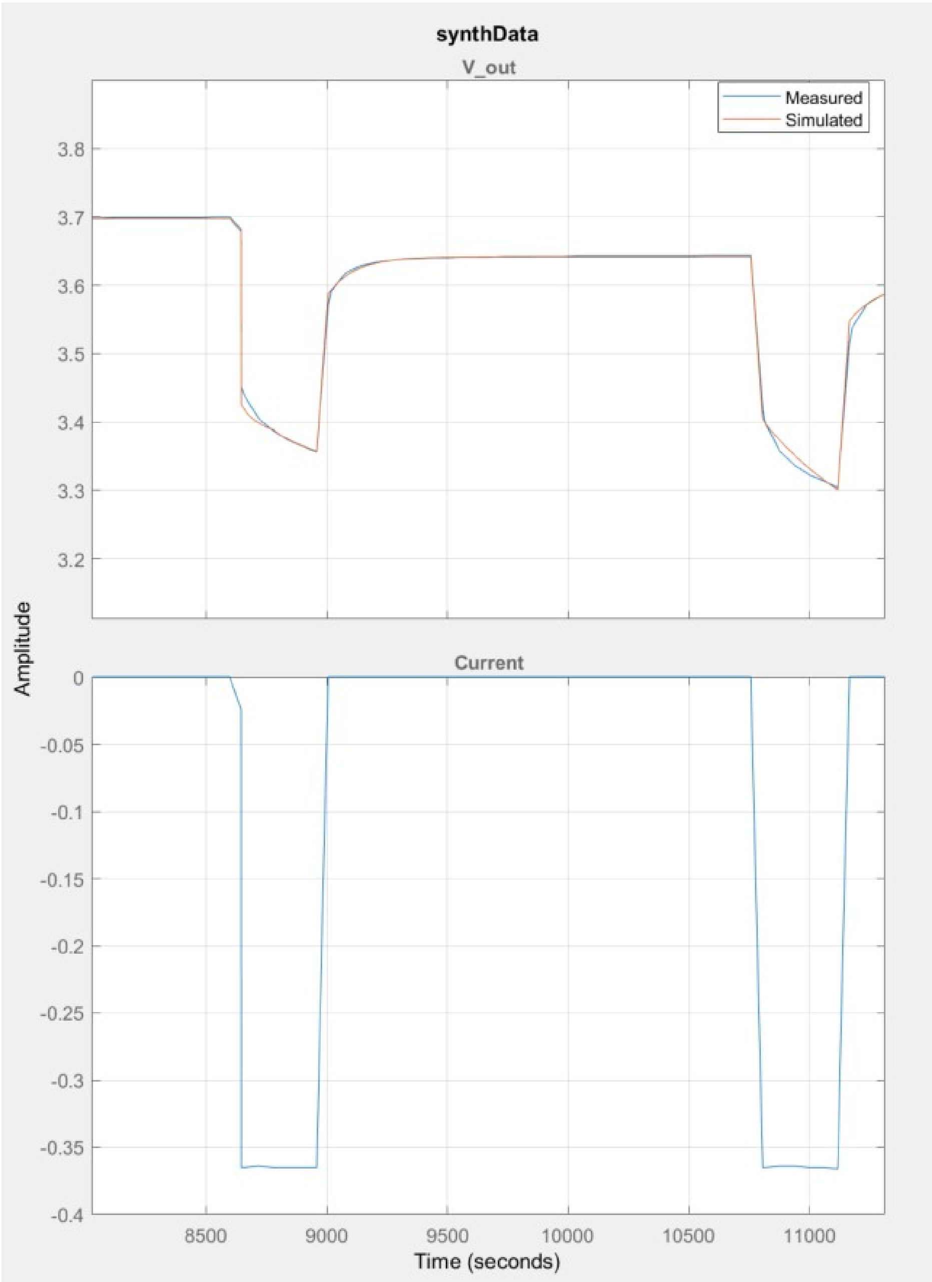



Figure 4.8: Closer look at the Measured and Simulated Curve for Final values using 2RC.

### 4.2.4 Validation using Parameter Estimation tool

The set of final parameter values obtained from the Parameter Estimation activity can be validated using another set of experimental data using Parameter Estimation tool. The result from the validation experiment is shown in Fig. 4.9. It is important to validate the data to avoid the threats to the internal validity of the experiment.

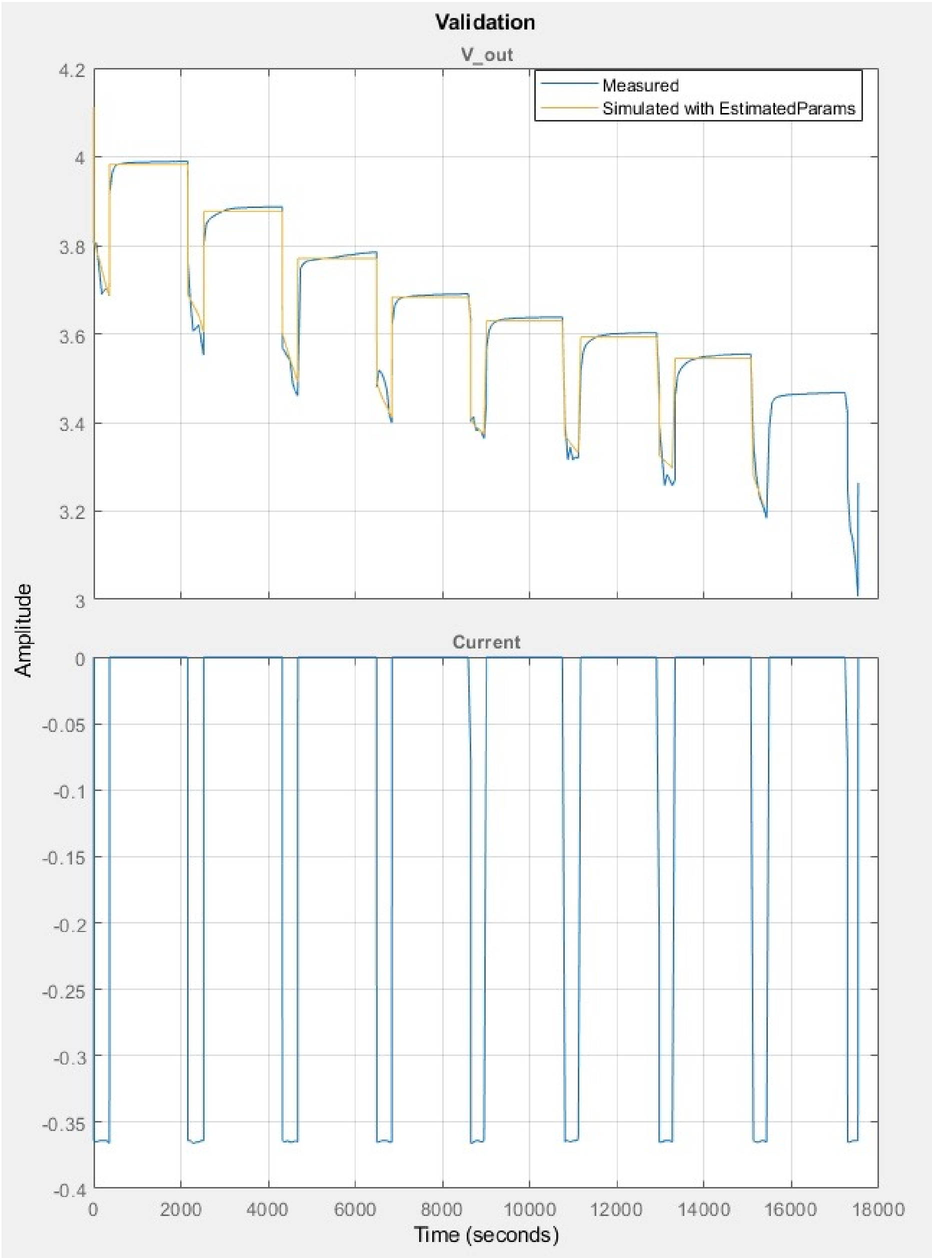



Figure 4.9: The result of validation experiment using a new set of data.

# Chapter 5

# Evaluation

Based on the model response to the experimental data which is presented in the previous chapter, it is clear that the model performs very well at both the levels of complexity for a given set of data values. For 1RC component, the model curve shows satisfactory result. It shows sufficient accuracy in comparison to the output shown by 2RC model. Whereas for 2RC component, the model showed high fidelity with the experimental data at the cost of greater complexity and execution time. Therefore, for portable electronic design application devices 1RC component is much more useful than 2RC component model. It is evident that the model is able to capture the dynamic characteristic with more accuracy when there are more RC component used. This is because the Simulink Design Optimization algorithm processes data points with more accuracy when the circuit consists of more RC components.

Battery management software use battery models to predict the remaining lifetime of the battery by measuring charge and discharge profiles. Although, it is difficult to estimate battery lifetime accurately for a particular device because over a period of time the energy demands of the applications vary significantly. Another factor which does not allow the accurate estimations is that the battery's chemical behavior vary when different types of load is applied. For example, if high load is applied to the battery, the battery will start behaving like a large capacitor and this will change the battery characteristics. Battery life prolongs when it operates on moderate current at constant rate rather than pulsed current at abrupt high load [35].

# Chapter 6

# Discussion

The main objective of this thesis is to answer the research questions mentioned in Section 1.2. The results from the experimental study shown in Chapter 4 can be used to answer the **first research question** which enquires about the non-linearity of the battery characteristics. The curves representing battery behaviour from the experiments show that the battery recovers to a great amount when left in idle state for small duration as low as ~6 min. The curves shown in Fig. 4.6 are collected from sensor battery pack with the help of Cadex 8000 Battery Analyzer. They show the dip in voltage when the current is drawn from the battery and then subsequently recovers during idle time. This effect is called Recovery effect and is one of the indicators of non-linear behaviour.

The non-linear behaviour is also due to the rate-capacity effect. This experimental study did not cover the effect of current with high C-rate on the discharge curve and capacity. This type of test can show that higher the discharge current, lesser the capacity of the battery. For future study, it will be interesting to uncover the recovery-effect and use it to design devices while keeping in mind the non-linear nature of battery. These factors highly contribute towards the fact that battery behaviour differs from each other, and also that no two batteries are alike.

The **second question** is about the design considerations when dealing with non-linear power sources. The experiment results show that the recovery effect is of great value for the systems which do not require constant power supply. For example, Handy et al. [18] has described the integration of battery model with energy model using Network Simulator [3]. The Network simulator (NS2) is a discrete event simulator which supports network scheduling, TCP, routing and other network related research work for wired and wireless networks. Traffic shaping algorithms such as the one mentioned in [24], helps utilize the *recovery effect* by interrupting the traffic as well as the discharge when the battery capacity reaches a certain threshold. And resumes the traffic once the capacity reaches to an extent that it can support at least one transmission.

This thesis explored various ways in which wireless sensor nodes and devices consume power, which answers the **third question** from the list. As discussed in Chapter 3 the communicating subsystem of the sensor devices consume a lot of energy. If the energy consumption problem of individual subsystems like communicating subsystem is not solved during early design phase, the poor design will penetrate deep into the system resulting in inefficient energy guzzling devices. Therefore, in order to be most effective, design decisions are made very early during design phase itself. Battery aware device designers collect varying energy profiles for the device based on its use in different setups. These energy profiles along with battery models are used to create battery aware devices. For example, the model can be used to determine the energy consumption of the wireless sensor network as explained in [28]. Park et al. [28] claim that the battery aware design which employs the battery characteristics to determine the transmission power levels of the sensor nodes, can improve the battery performance by ensuring 52% increase in *data transmission*. The claim is based on the premise that in a wireless sensor network the power level at which the sensor nodes transmit and receive data governs the battery consumption of the devices. If the sensor nodes transmits at higher power level than the required level, the rate of discharge from the battery increases. This also reduces the battery capacity due to the *rate-capacity effect*. However, the data transmission will be error prone if it takes place below the required power level, resulting in multiple attempts of re-transmission. These attempts will lead to rapid depletion of the energy source [33]. Our experimental study does not cover this aspect of energy consumption, however, a theoretical background is presented for future studies.

Similarly, the developers may use various techniques to control the battery power misuse. For example, as suggested by Lahiri et al. [24], battery models can be used to govern CPU frequency scaling. This requires that the lower bound on CPU clock frequency is redefined to maximize a metric combining battery capacity, performance and power. The lower bound of CPU clock frequency results into discharge pulses from the battery which prolongs the battery life. In a separate implementation, current discharge profiles obtained from the system can be combined with battery characteristics from battery models to enable *battery-aware static task scheduling*. This type of scheduling is static because the tasks are scheduled based on previously collected current discharge profiles. However, scheduling can be made dynamic by combining the feedback from the battery during runtime. This is also known as *Dynamic*

*Power Management.*

In order to answer the **fourth question**, we selected equivalent circuit model to represent the real behaviour of the battery given a particular energy profile. The Chapter 4 showed how can we use the ECM to determine the complex nature of the battery. The model response in Fig. 4.8 clearly shows the success of the 2RC model. However, apart from monitoring and measuring battery performance with respect to the device functions, there are ways to improve the life of the sensor devices. A brief discussion is presented in the section below.

The various techniques discussed in this section can be used to design battery aware devices. The results from the experiment shows that the battery behaviour can be modelled using ECM. This model can then be combined with load profiles from the actual devices to see the effect of load on battery life. For example, Aldeer et al. [7] have shown a technique to tackle the energy consumption in patient monitoring devices based on the principle of *collaborative sensing*. In this technique they used two distinct motion detection sensors to capture the motion of the patient. The first sensor is the ball tube analog motion sensor which consumes no-energy and provide low-accuracy data, mounted on second high efficiency Inertial Measuring Unit (IMU) which includes a group of sensors like accelerometer, gyroscope and magnetometer. The energy hungry IMU sensor does not wake up until the sensing data obtained by ball-tube sensor reaches a certain threshold. Thereby saving a lot of power drawn from the battery. The energy profile obtained from this collaborative sensing can be used as an input to the battery model to study various ways to optimise the sensing in the sensor nodes. In their paper, Aldeer et al. [7] have assumed battery Lifetime as a linear function of Capacity and Current, which is not a case with real batteries and therefore, it requires a proper study with appropriate battery model. Similarly, Patient Activity Recognition and Classification can also be used as an input to the battery model in the form of Energy profile. Using Machine Learning for the activities classification, the system can be trained to optimize the battery consumption during activities which require less amount of monitoring.

## Battery handling and storing

In order to continue the discussion from Section 3.2, here are some important insights into the user interactions with batteries. Environmental conditions govern the longevity of lithium-ion batteries to a great extent. Elevated temperatures destroy the internal chemical properties of the battery. Capacity fade is the cause of slow decline in the runtime of the battery.

Electric vehicles and satellites operate on lower charge voltages. These lower charge voltages favors the long battery life. It can also be beneficial to keep the voltages lower for consumer devices, but such provisions are seldom offered; as a result planned obsolescence takes care of this. Planned obsolescence, as defined earlier, is the practice where products (in our case, batteries of medical equipment) are often discarded much before their remaining useful lifetime in order to prevent indefensible breakdown [11].

From the point of view of human-computer interaction, Shepard et al. [42] presented a method called *LiveLab* in which they measured e.g. call time, text frequency and other application usage of smartphones based on the time and location. They also measured wireless network usage to gain more insight into the study of human interaction with devices. They found out that time and location can provide unique information related to how the human interact with their devices. In wireless patient monitoring system, example from *Livelab* can be used to record and classify the activity of the device based on the time and location. For example, during the night, the activity of the patient is less as compared to the day time, which means that heart rate is constant for longer duration. This suggests that the battery requirement is not at its peak because the system must not ping frequently for new information. The system wake-ups can be programmed considering the health and state of the patient. The health can be a factor in determining or guessing the future power consumption. A patient profile can be created in the logger and using machine learning techniques and the patient profile, optimum battery expenditure can be planned.

However, a similar study conducted by Vallina-Rodriguez et al. [45] proved that such resource management is complicated and not feasible on mobile devices, therefore it is unlikely that activity classification based resource management is possible in patient monitoring unless it is based on fine-grained information from the system which is user-centric, system-centric and highly contextual.

# Chapter 7

# Conclusions

Towards the end, here are some important lessons learnt while studying for this topic. These lessons or guidelines must be taken care of when discharging the batteries, in order to prevent unexpected battery outcomes. First, the heat increases battery performance but shortens life by a factor of two for every 10C increase above 25–30C (18F above 77–86F) this is known as the "10C increase = half life" rule [11]. Therefore, it is advisable to always keep the battery cool. In order to prevent electrical short due to cell reversal it is required to prevent from over-discharging. Use of a larger battery is recommended when the device poses high load and repetitive full discharges. Batteries are suitable for moderate direct current (DC) discharges. They exhibit the characteristics of capacitor when discharging at high frequency. They are unsuitable for pulse and heavy momentary loads. Additionally, utilization based power consumption is not the only way in which hardware component consumes Power. There are other external factors such as signal strength of Wifi or system calls which alters the power state and thus cause power consumption. For example, the NIC device driver may adjust the transmission power when the signal strength changes. These points, in addition to developing a suitable battery model are very important for better portable sensor system design.

In this study, we have described various ways power expenditure takes place in portable systems. Then, we showed how the power expenditure of medical sensor devices is related to the battery behavior. For this we used the concept of battery modeling and showed how the battery models can be used to simulate the real batteries for calculation of different parameters. Electric circuit models are better when compared to mathematical models and the physical ones. They provide better solution in terms of tradeoff. When compared with physical models, electric circuit models are less complex and provide a medium accuracy [36]. Another benefit of electric circuit model is that they are simple to implement for real time applications. The model used is an isothermal model which is a very popular equivalent circuit model mainly used for electrical vehicles. It is shown in the study that by tweaking some of the input parameters. The HJGC model [20] can also be used with good accuracy and flexibility to represent different types of batteries. Construction and validation of a pack of circular cell battery is described in previous chapters. Simulation results show the model is able to very well represent the experimental data.

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# Appendix A

# Table comparing SOC estimation techniques

A table comparing SOC estimation techniques is shown below.

| Technique | Field of application | Advantages | Drawbacks |
|---|---|---|---|
| Discharge test | All battery systems<br>Used for capacity determination in the beginning of life | Easy and accurate, independent of SOH. | Offline, time intensive, modifies the battery state, loss of energy |
| Ah balance | All battery systems, most applications (consumer, PV, EV). | Online, easy, accurate if enough re-calibration points are available and with good current measurement. | Needs a model for the losses.<br>Sensitive to parasite reactions.<br>Cost intensive for accurate current measurement<br>Needs regular re-calibration points |
| Physical properties of electrolyte (density, concentration, colour) | Lead, possibly Zn/Br and Va | Online<br>Gives information about SOH | Error if acid stratification. Low dynamic. Problem of stability of sensors in electrolyte. Sensitive to temperature and impurities. |
| Open circuit voltage | Lead, Lithium, Zn/Br and Va | Online, cheap | Low dynamic, error if acid stratification and needs long rest time (current =0) for lead system. Problem of parasite reaction (e.g. Sb poisoning by lead) |
| Linear model | Lead PV, possibility for other battery systems ? (not tried yet) | Online, easy | Needs reference data for fitting parameters |
| Artificial neural network | All battery systems | Online | Needs training data of a similar battery |
| Impedance spectroscopy | All systems | Gives information about SOH and quality. Possibility of online measurement. | Temperature sensitive, cost intensive. |
| D.C. Internal resistance | Lead, Ni/Cd | Gives information about SOH, cheap. Possibility of online measurement. Easy | Good accuracy, but only for low SOC |
| Kalman filter | All battery systems, PV, dynamic applications (e.g. HEV) | Online. Dynamic | Needs large computing capacity.<br>Needs a suitable battery model.<br>Problem of determining initial parameters |

Table A.1: Various SOC estimation techniques and their comparison [29].

# Appendix B

# Figures showing Parameter Curves

After the estimation of Final Values, the resulting simulated curve is also shown in MATLAB software. This curve is shown in Fig. 4.6 and Fig. 4.7. The corresponding Estimated parameters curve is shown in Fig. B.1 and Fig. B.2.

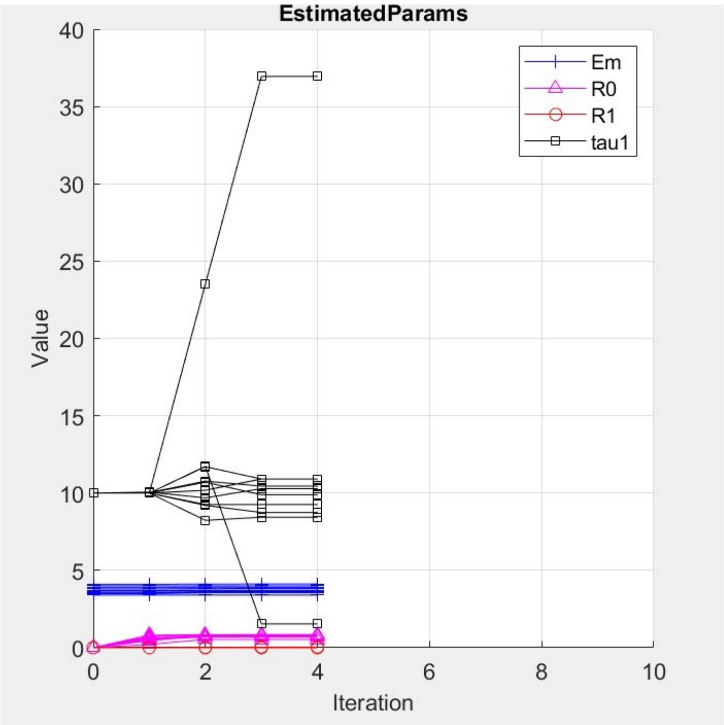


Figure B.1: Parameter Estimation Curves for Final values using 1RC.

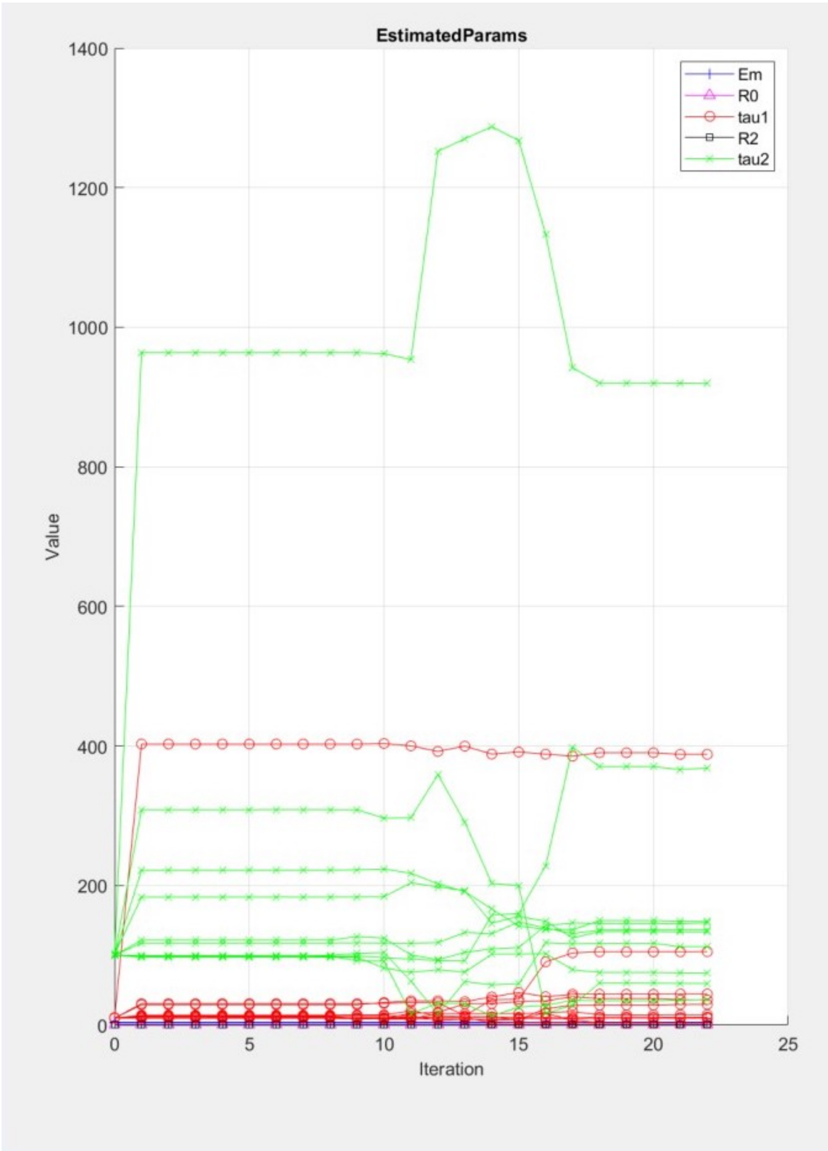


Figure B.2: Parameter Estimation Curves for Final values using 2RC.